Climatologically Aided Mapping of Daily Precipitation and Temperature

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ABSTRACT

Accurately mapped meteorological data are an essential component for hydrologic and ecological research conducted at broad scales. A simple yet effective method for mapping daily weather conditions across heterogeneous landscapes is described and assessed. Daily weather data recorded at point locations are integrated with long-term-average climate maps to reconstruct spatially explicit estimates of daily precipitation and temperature extrema. The method uses ordinary kriging to interpolate base station data spatially into fields of approximately 2-km grain size. The fields are subsequently adjusted by 30-yr-average climate maps [Parameter-Elevation Regression on Independent Slopes Model (PRISM)], which incorporate adiabatic lapse rates, orographic effects, coastal proximity, and other environmental factors. The accuracy assessment evaluated an interpolation-only approach and the new method by comparing predicted and observed values from an independent validation dataset. The results of the accuracy assessment are compared for a 24-yr period for California. For all three weather variables, mean absolute errors (MAE) of the climate-imprint method were considerably smaller than those of the interpolation-only approach. MAE for predicted daily precipitation was ± 2.5 mm, with a bias of $+0.01$. MAE for predicted daily minimum and maximum temperatures were $\pm 1.7°$ and $\pm 2.0°$C, respectively, with corresponding biases of $-0.41°$ and $-0.38°$C. MAE differed seasonally for all three weather variables, but the method was stable despite variation in the number of base stations available for each day.

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1. Introduction

Accurately mapped meteorological data are an essential component of hydrologic and ecological research conducted at broad scales (Thornton et al. 1997). Spatially explicit maps of long-term-average climate are becoming increasingly available (e.g., Daly et al. 1994, 1997, 2000), but many broad-scale hydrologic and ecological studies require meteorological variables, such as precipitation and temperature, to be mapped on a daily-time-step, or even finer, temporal scale (Running et al. 1987; Running and Coughlan 1988; Band et al. 1991; McMurtrie et al. 1992). Maps of daily weather conditions are critically important for models of earth surface processes and biological population dynamics that respond directly to short-term variability in weather rather than average climate. There are a variety of methods to map daily weather conditions; however, each has limitations for applications over broad scales.

Geostatistical interpolation (e.g., kriging) is one approach to estimate weather conditions at unsampled locations (Phillips et al. 1992; Goovaerts 2000), but its application for large regions is limited by low densities of base stations, especially where the distribution of base stations is unrepresentative of topographic variability and geographic features (Dodson and Marks 1997; Daly et al. 2002). Models such as Mountain Climate Simulator (MTCLIM) have been developed to provide daily values for weather variables in complex terrain (Running et al. 1987; Hungerford et al. 1989; Glassy and Running 1994), but assumptions of their method can break down over large areas (>2000 km^2; Thornton et al. 1997). At the cost of considerable complexity, the "Daymet" model extends MTCLIM logic to include interpolations between multiple observations across larger regions for mapping daily meteorological variables (Thornton et al. 1997). Others have integrated

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long-term-average climate data to improve interpolations of annual average temperatures (Willmott and Robeson 1995), but this approach has not been presented for mapping weather conditions on a daily time step.

This paper presents a method for mapping daily weather conditions that integrates a network of base station point observations with long-term-average climate maps. The method is designed to utilize readily accessible base station data and a spatial climate dataset [Parameter-Elevation Regression on Independent Slopes Model (PRISM); Daly et al. 1994] that captures the effect of variable terrain and geographic features, such as coastal proximity and orographic patterns. To evaluate the predictive accuracy of this method, we examined the following three questions:

1) How accurately does the method predict daily weather conditions in comparison with an interpolation-only approach?
2) To what extent does the error in weather estimates differ seasonally for each method?
3) To what degree is the magnitude of error consistent from day to day, given a variable number of available sample points?

The accuracy assessment evaluates the straightforward interpolation-only approach and the new method by comparing predicted values with observed values from an independent validation dataset. The results of the accuracy assessment are compared seasonally and annually over a 24-yr period (1980–2003).

2. Methods

a. Meteorological and climate data

The National Oceanic and Atmospheric Administration (NOAA) National Climatic Data Center (NCDC) provides daily weather data for a network of first-order and cooperative weather stations in California. These weather stations were downloaded and mapped in a geographic information system (GIS) for California (Fig. 1). The database contains 24 yr of daily weather parameters (1980–2003) at 779 point locations. Any given day of the record typically contains between 131 and 234 stations with complete data. NCDC observations may present some problematic characteristics, such as variable time of observation, uncertainty in conversion of snow depth to liquid precipitation, and unshielded gauges, and data quality varies by station and time period. For the purposes of this study, the data were considered to be generally reliable without additional quality control. Additional weather networks
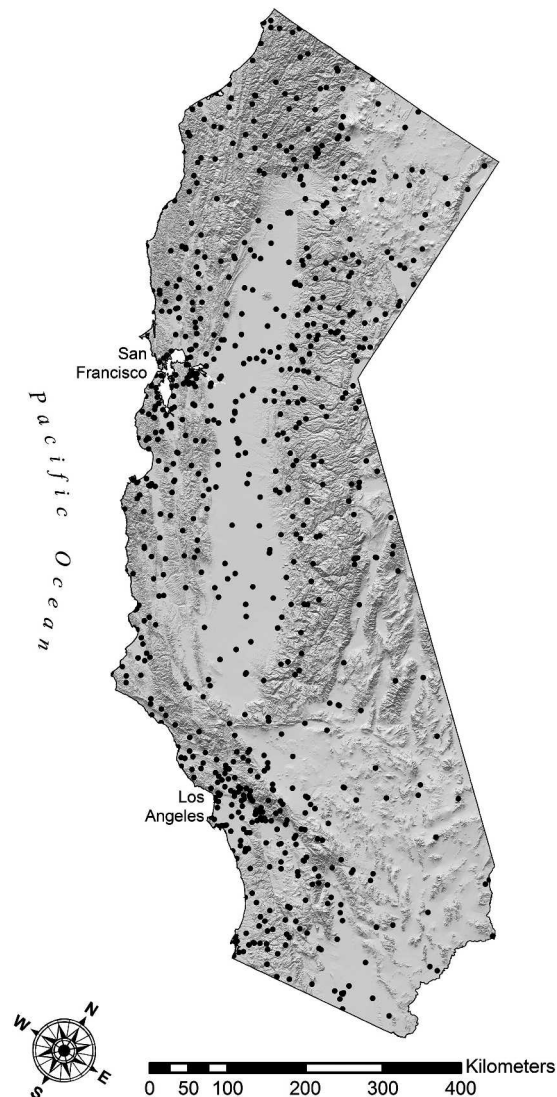

FIG. 1. Map of 779 weather base stations with daily observations from NOAA NCDC in California (1980–2003).

and sources could potentially augment station density but were not included so as to minimize complexity in the database construction process.

Long-term-average climate maps are available for many regions across the world. For this research, we have used climate maps produced by PRISM (Daly et al. 1994, 1997, 2000) (Fig. 2). PRISM uses 30 yr of climate observations from weather base stations in conjunction with digital terrain data and other environmental factors to interpolate climatic variability spatially across a landscape. Grain size of each PRISM grid cell is approximately 2 km × 2 km. The PRISM method assumes that elevation is among the most important factors controlling landscape patterns of temperature and moisture, and it uses linear regression to estimate
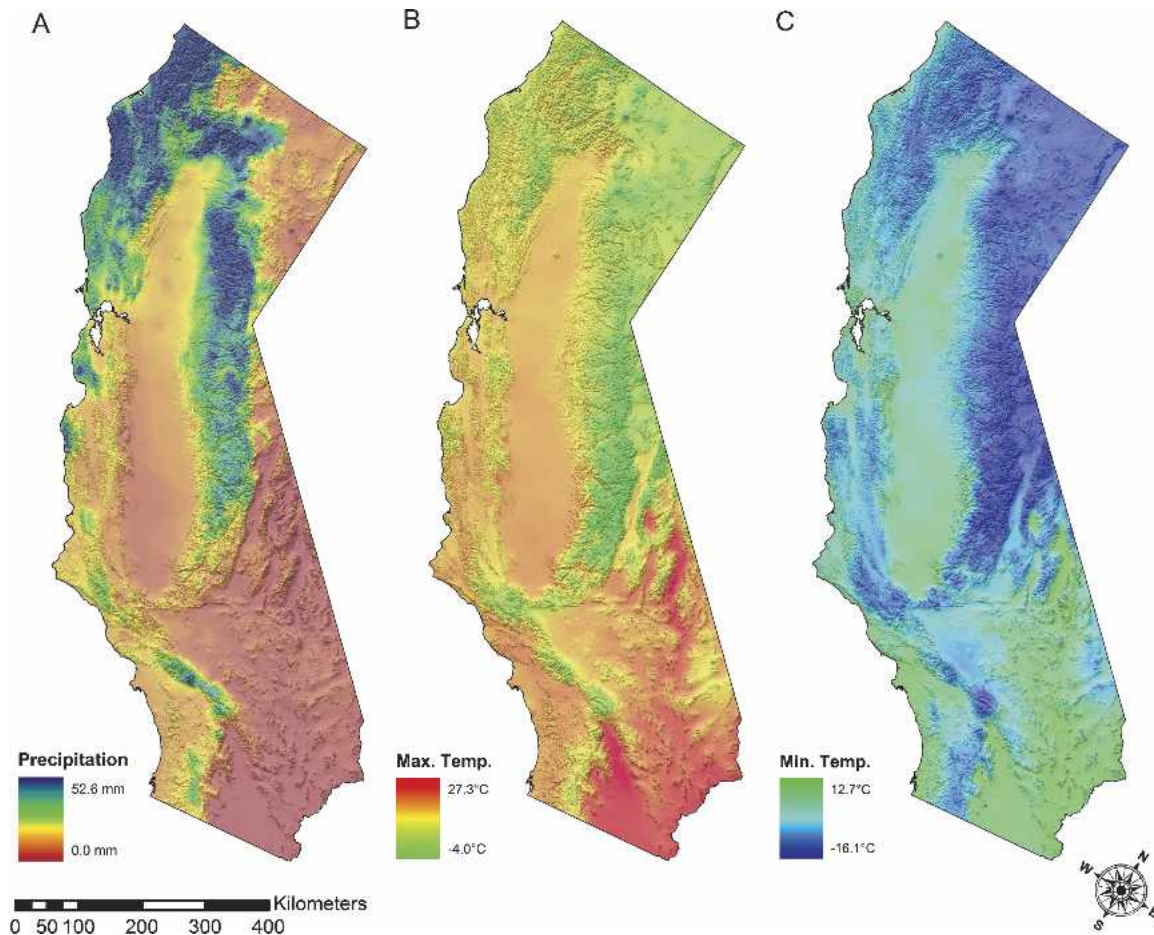
FIG. 2. Climate variables for Mar from PRISM: 30 yr (1961–90) monthly mean of (a) total precipitation, (b) maximum temperatures, and (c) minimum temperatures.

climate variability within local topographic orientations, or facets. Other environmental factors are incorporated using differential regression weighting of the base station data points. The combined weight of a station is a function of elevation, coastal proximity, aspect, local relief, and vertical airmass layering. PRISM captures the influence of large water bodies, complex terrain, and atmospheric inversions in determining temperature and moisture, including rain shadow effects. These factors are especially important in California, where climate varies considerably over short distances.

b. Mapping methods

1) INTERPOLATION ONLY (IO)

To produce spatially explicit maps of precipitation and maximum and minimum temperatures, ordinary kriging was used to interpolate the point observations from a network of weather base stations (Fig. 3). The software used for all interpolations was ArcInfo, version 8.3, produced by Environmental Systems Research Institute. We developed a script in Arc Macro Language to automate the processing of each weather variable for all days using the kriging command of the software's "GRID" module. Kriging and its variants (Matheron 1971) have been frequently used to interpolate point measurements spatially in numerous earth system science applications (e.g., Bonham-Carter 1994; Burrough and McDonnell 1998; Isaaks and Srivastava 1989). Kriging has also been applied extensively to the interpolation of climate data (e.g., Dingman et al. 1988; Hevesi et al. 1992; Phillips et al. 1992; Garen et al. 1994). Kriged estimates for a spatially distributed variable at any unmonitored location are computed as a weighted average of the known values from a surrounding set of sampled points. Kriging weights are derived from a statistical model of spatial correlation expressed as semivariograms that characterize the spatial dependency and structure in the data (Fig. 4). Weights are derived such that the kriged surface minimizes the error
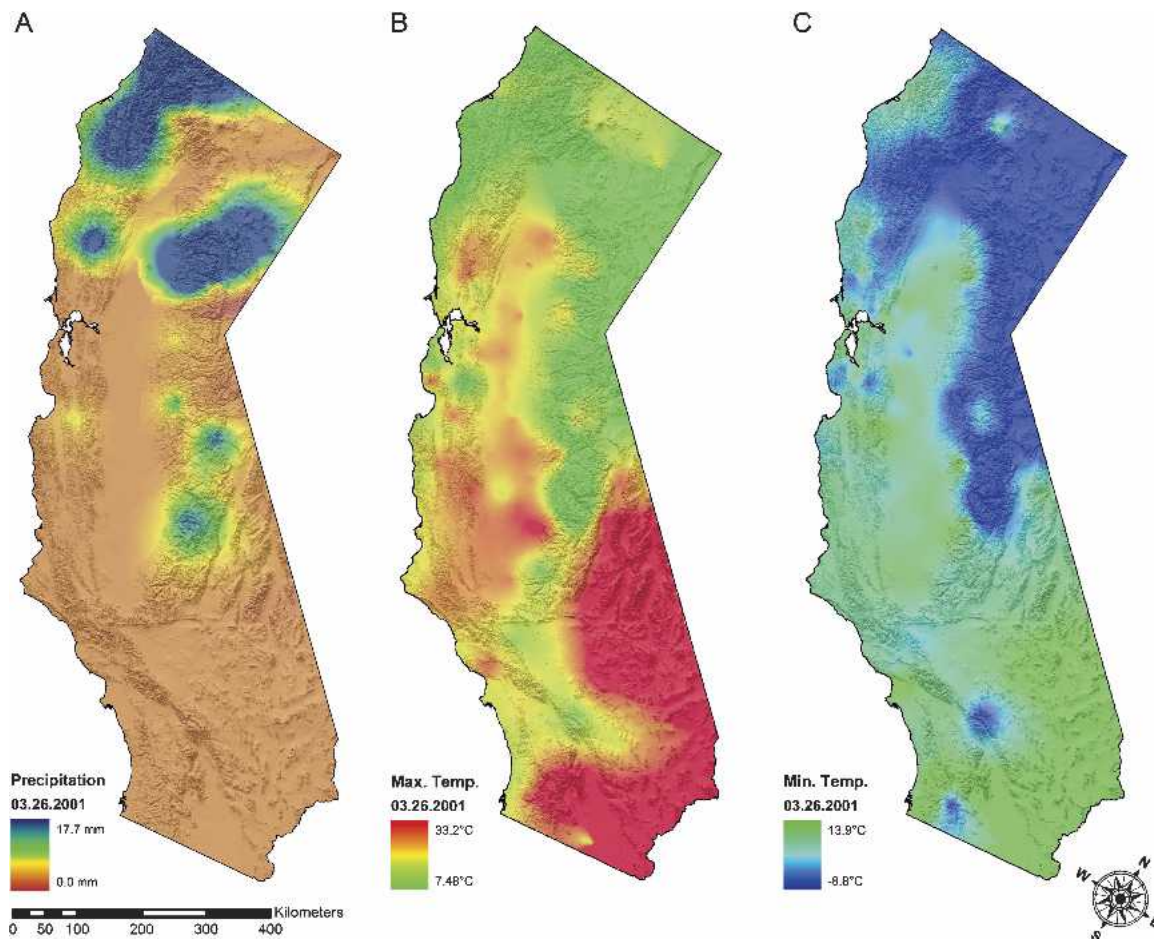
FIG. 3. Prediction maps using the interpolation-only method to interpolate daily base station data for (a) precipitation, (b) maximum temperatures, and (c) minimum temperatures: 26 Mar 2001.

variance and the estimator is unbiased at any unsampled location within the spatial domain. Kriging assumes that the observations are realizations of a stationary stochastic process and that predictions have standard errors and probabilities associated with them. Although the fit of the interpolation is limited by the fit of the estimated semivariogram to the actual semivariances from sampled point data, it is generally held that spatial predictions are robust with respect to misspecification of the semivariogram model (Cressie 1993; Goovaerts 1997). A major strength of the method is that measured spatial dependence in the weather parameter of interest is used to inform the prediction.

2) CLIMATE IMPRINT (CI)

For our work, the long-term (30 yr) average values on PRISM maps provide a "spatial imprint" to represent environmental gradients at unsampled locations for which NCDC base station data do not exist. The

PRISM maps are combined with the output of a kriging interpolation process to incorporate PRISM's environmental relationships into the final predictive maps.

(i) CI precipitation

The equation used to calculate daily input values is simply expressed as the ratio of the daily weather observation to the long-term-average value for that month:

$$P_{\text{ratio}} = P_{\text{daily}}/P_{\text{monthly}} ,$$

where P_{daily} is the daily base station NCDC value and P_{monthly} is the 30-yr monthly mean from PRISM at the base station.

Ordinary kriging is then used to interpolate a gridded surface of P_{ratio} for a given day that visually resembles the output of the interpolation-only method shown in Fig. 3. The kriging output is subsequently multiplied by
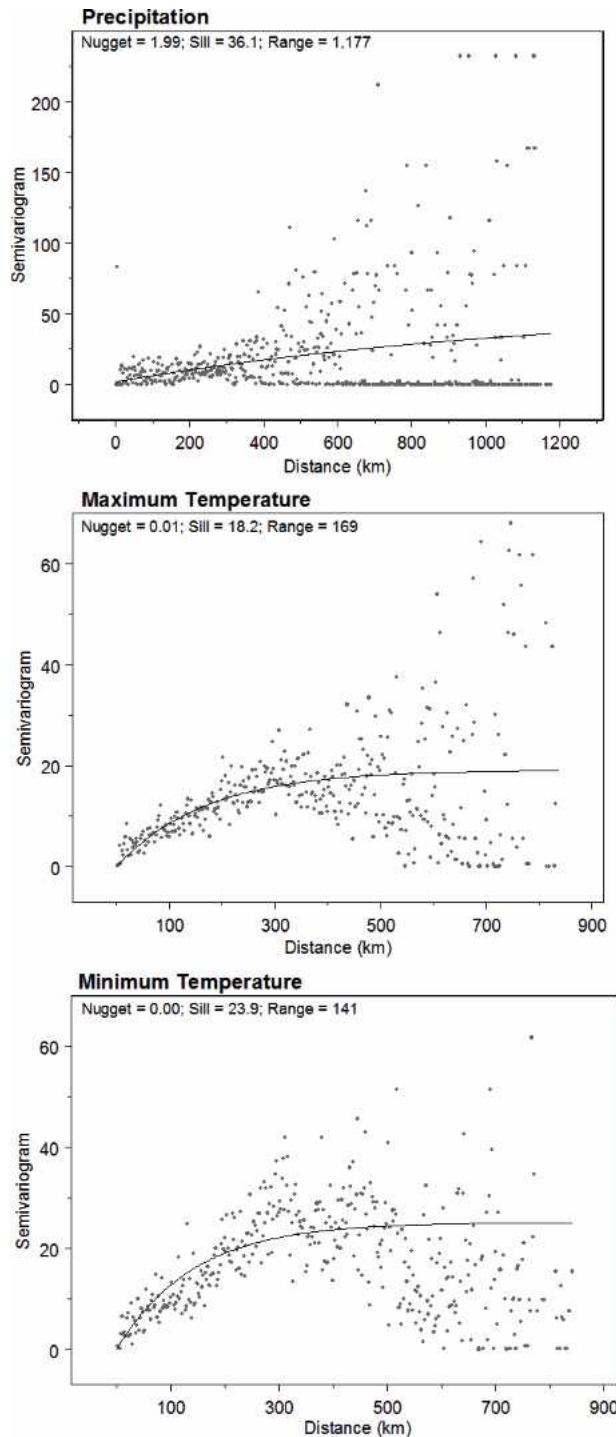
FIG. 4. Experimental exponential (solid line) and empirical (dots) semivariograms for daily values of (top) precipitation, (middle) maximum temperature, and (bottom) minimum temperature on 26 Mar 2001.

the PRISM grid to derive a map of predicted daily precipitation values (Fig. 5a):

$$P_{\text{daily}} = P_{\text{interpolated ratio}} \times P_{\text{monthly}},$$

where $P_{\text{interpolated ratio}}$ is the amount of precipitation during the day relative to the monthly mean for that location.

(ii) CI temperature

Maximum and minimum temperatures are computed in a similar fashion as precipitation, but instead the input values for a given day are calculated as the difference between the monthly mean (minimum or maximum) temperature and the observed daily value:

$$T_{\text{difference}} = T_{\text{monthly}} - T_{\text{daily}},$$

where T_{daily} is the daily NCDC base station value and T_{monthly} is the long-term monthly mean maximum or minimum temperature at the base station location. These values are input to the kriging model that interpolates a surface of difference values for the entire state. This grid surface is subtracted from the PRISM map of long-term monthly means to derive a map of predicted daily minimum or maximum temperature values (Figs. 5b, 5c):

$$T_{\text{daily}} = T_{\text{monthly}} - T_{\text{interpolated difference}},$$

where $T_{\text{interpolated difference}}$ is the kriging output of temperature differences.

c. Accuracy assessment

Daily weather conditions of precipitation and minimum and maximum temperatures were predictively mapped using both methods over the 24-yr period (1980–2003). For each day, 10% of the available base stations were randomly withheld from the predictive models to form an independent validation dataset. To assess predictive accuracy, predicted values were compared with observed values in the validation dataset for a subset of days representing a seasonal range of conditions over this period. Daily precipitation predictions were assessed for 1 week (days 20–26) in each of the wettest months of the year: December, January, February, and March. For minimum and maximum temperatures, the model was tested on 7 days per season (days 20–26) or 4 weeks per year in the following months: December, March, June, and September. Each parameter was evaluated for 28 days per year, or 672 total days over the 24-yr period.

To address question 1, we compared predicted values from each daily weather map over the 24-yr period to the observed values in the validation dataset using
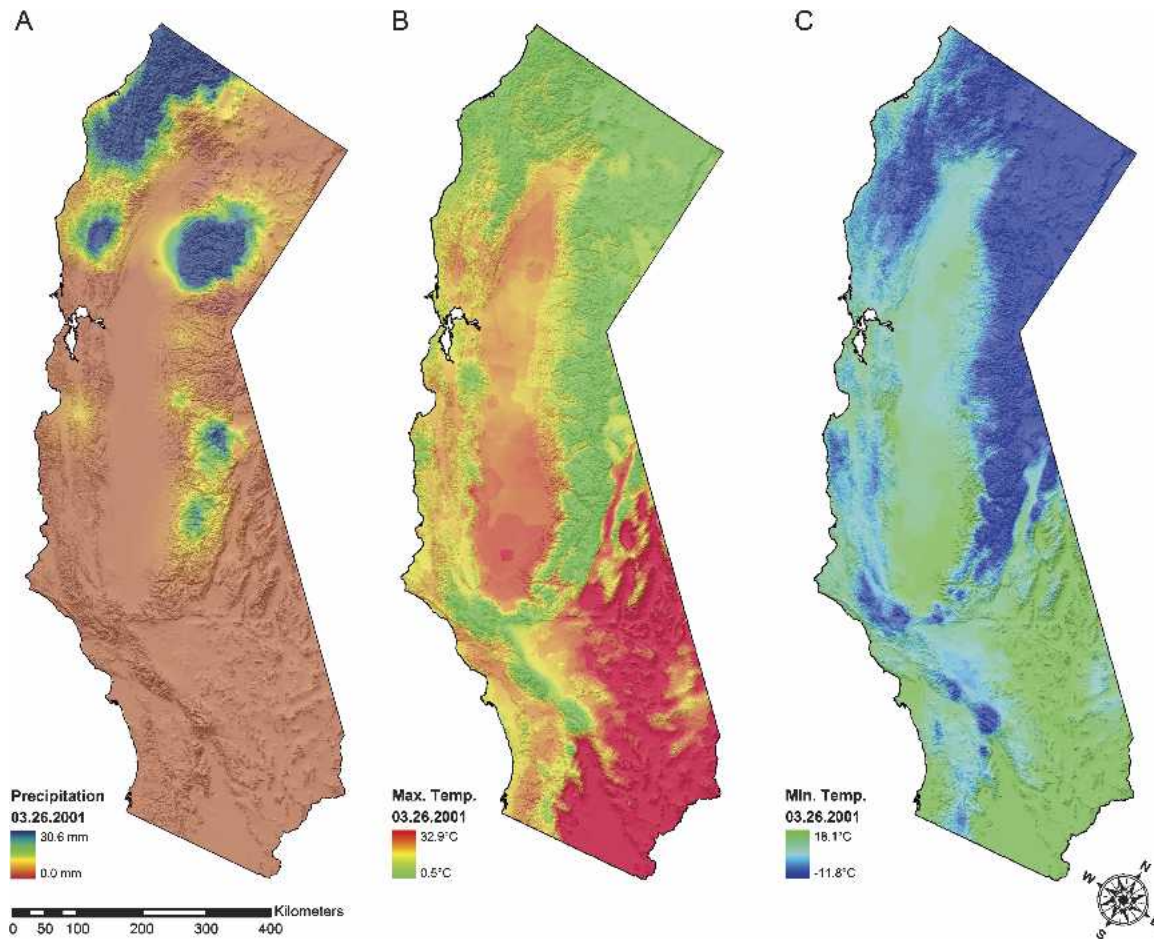
FIG. 5. Prediction maps using the climate-imprint method to integrate PRISM with daily base station interpolation for (a) precipitation, (b) maximum temperatures, and (c) minimum temperatures: 26 Mar 2001.

three statistics. First, the coefficient of determination (r^2) was calculated with linear regression to assess the amount of variability in observed values accounted for by the model. Second, mean absolute error (MAE) was computed to determine overall magnitude of error:

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^{n} |(P_i - O_i)|,$$

where n is the number of samples, P_i is the predicted weather value, and O_i is the observed weather value. Third, mean error (MER) was calculated to identify tendencies of under- versus overprediction, or overall directionality of error:

$$\text{MER} = \frac{1}{n} \sum_{i=1}^{n} (P_i - O_i).$$

Positive and negative MER values indicate over- and underprediction, respectively.

To address question 2, one-way analysis of variance (ANOVA) was used for each weather parameter to determine the degree to which MAE and MER differ between months (the grouping factor). The replicates within month were considered to be independent because they were randomly selected from a population of possible sites for inclusion in the validation dataset. To investigate question 3, we computed Spearman's coefficient of rank correlation (r_s) to examine whether there is a monotonic relationship between the number of input base stations and the MAE.

3. Results

a. Precipitation

1) INTERPOLATION ONLY

Regression analysis showed that the interpolation-only approach predicted 59% of the variability in observed daily values of precipitation with a slight tendency to underestimate (MER = −0.04; Table 1).

TABLE 1. Performance comparison of IO and CI models for precipitation, maximum, and minimum temperatures.

	r^2; p		MAE		MER	
	IO	CI	IO	CI	IO	CI
Precipitation	0.59; <0.0001	0.64; <0.0001	2.8 mm	2.5 mm	−0.04	0.01
Max temperature	0.85; <0.0001	0.92; <0.0001	2.7°C	2.0°C	−0.07	−0.38
Min temperature	0.79; <0.0001	0.89; <0.0001	2.2°C	1.7°C	−0.09	−0.41

MAE calculations indicated that daily precipitation predictions were, on average, within ±2.8 mm of observed. ANOVA identified a significant difference in MAE between months ($F = 15$; $p < 0.0001$) (Fig. 6a). The number of available input base stations varied from day to day because of incomplete data, ranging from 166 to 234. Testing of the Spearman's correlation coefficient showed a weak trend of reduced MAE with more stations ($r_s = -0.08$; $p = 0.05$).

2) CLIMATE IMPRINT

Regression analysis showed that the climate-imprint precipitation model predicted 64% of the variability in observed daily values with a slight tendency to overestimate (MER = 0.01; Table 1). MAE calculations indicated that the model predicts daily precipitation, on average, to within ±2.5 mm of observed. Approximately two-thirds of the comparisons between the predictions and observations were within 1 mm, and about 93% of the predicted daily values were within 10 mm of observed. In addition, ANOVA identified a significant difference in MAE between months ($F = 11.2$; $p < 0.0001$). According to Spearman's rank correlation coefficient, there is a weak monotonic relationship between MAE and number of stations, in the negative direction ($r_s = -0.08$; $p = 0.05$).

b. Temperature

1) INTERPOLATION ONLY

The maximum and minimum temperature interpolation-only models predicted 85% and 79% of the variation in observed daily values, respectively (Table 1). On average, maximum and minimum temperature are slightly underpredicted (MER = −0.07 and −0.09; Table 1). MAE calculations showed that maximum temperature predictions of interpolation-only models were, on average, ±2.7°C of observed, and predicted minimum temperatures were ±2.2°C of observed. ANOVA identified a significant difference in MAE between seasons for both maximum ($F = 67$; $p < 0.0001$; Fig. 6b) and minimum ($F = 7.0$; $p < 0.0001$; Fig. 6c) temperatures. Mean monthly absolute error values for minimum temperatures varied less than those for maximum temperatures. Because of incomplete data,

differences in the number of input base stations used ranged from 131 to 197 for minimum temperature and from 130 to 198 for maximum temperature. For maximum temperature, Spearman's correlation coefficient
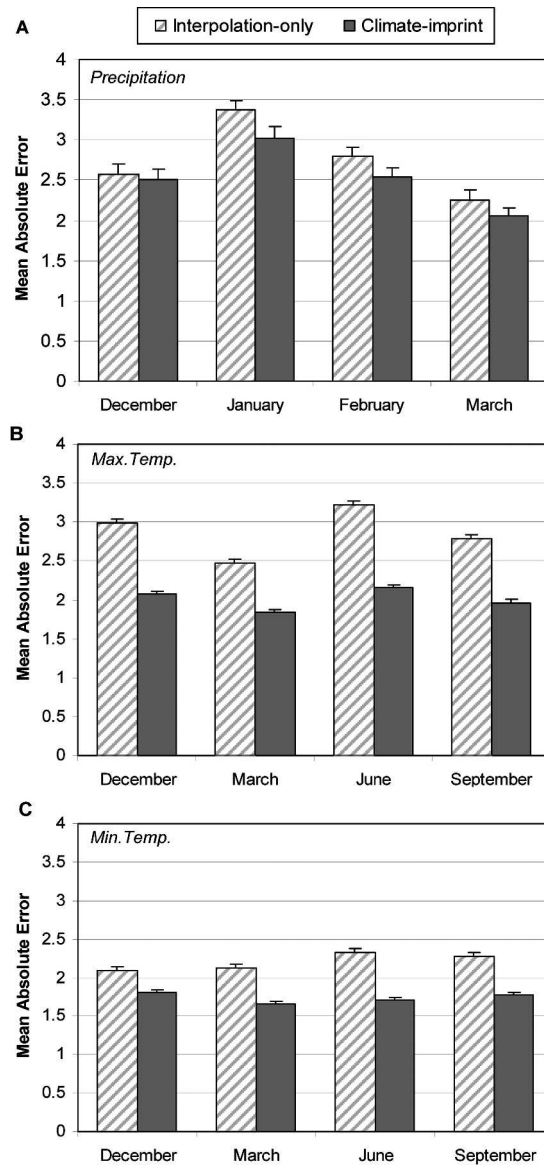

FIG. 6. Mean absolute error by month in daily estimations of (a) precipitation, (b) maximum temperatures, and (c) minimum temperatures for both interpolation-only and climate-imprint methods. Values are means with standard error bars.

showed a weak monotonic relationship between MAE and the number of stations, in the positive direction (r_s = 0.07; p = 0.07). For minimum temperature, the correlation coefficient indicated no relationship (r_s = −0.02; p = 0.57).

2) CLIMATE IMPRINT

The climate-imprint models for maximum and minimum temperatures predicted 92% and 89% of the variation in observed daily values, respectively (Table 1). On average, maximum and minimum temperatures were underpredicted (MER = −0.38 and −0.41; Table 1). The MAE showed that maximum temperature predictions were, on average, within ±2.0°C of observed, and predicted minimum temperatures were within ±1.7°C of observed. The distributions of absolute error for both maximum and minimum temperatures were similar; approximately one-third of the predicted temperatures were accurate to within 1°C, and more than 93% were within 5°C of observed values.

ANOVA indicated that MAE differed between seasons for both maximum (F = 14; p < 0.0001) and minimum temperatures (F = 4.0; p < 0.01). Mean monthly absolute error values for minimum temperatures varied less than those for maximum temperatures. For both temperature parameters, Spearman's correlation coefficient showed a weak monotonic relationship between MAE and the number of stations, in the positive direction (maximum temperature: r_s = 0.16; p < 0.001; minimum temperature: r_s = 0.20; p < 0.001).

4. Discussion and conclusions

The method that integrates long-term-average climate data with the interpolated base stations (climate imprint) performed better than the interpolation-only approach, predicting 5%–10% more variation in the daily weather parameters. In comparison with the IO method, the CI process increased the coefficient of determination (r^2) for maximum and minimum daily temperatures from 0.85 to 0.92 and from 0.79 to 0.89, respectively. Minimum temperature predictions experienced the greatest overall improvement in accuracy from the climate-imprint technique (+10%). Performance of the climate-imprint precipitation method was notably lower at 64% of the variation, but integration of climate data moderately increased the predictive accuracy of the interpolation-only approach from 59%. This improvement in predictive accuracy translated to noteworthy differences in mean absolute error as well: the climate-imprint method was, on average, 0.5°–0.7°C more accurate in predicted temperatures and 0.3 mm

more accurate for precipitation than the interpolation-only method. These quantitative differences between the output maps were visually evident, especially in regions of variable terrain lacking base stations (Fig. 7).

These results are encouraging given the simplicity of the climate-imprint method, which can be easily applied in a GIS environment. All that is necessary are readily available maps of climate and a network of daily weather conditions at point locations. Further updates and improvements to NCDC and PRISM datasets could increase the accuracy of the climate-imprint method. The method's readily available required elements allow for the reconstruction of daily weather conditions over long time scales and allow the creation of ongoing daily weather maps in near–real time.

The low density of base stations (1.9 stations per 1000 square kilometers) and the pronounced environmental variability in California present a challenging test for predictive mapping of daily weather conditions. The result that both approaches, in general, predicted less variation in precipitation than in temperature suggests that precipitation may be more spatially variable than temperature at the scale of the mapping process, which is illustrated by the semivariograms (Fig. 4). Precipitation patterns may also be more temporally dynamic than temperature patterns, which could account for much of the unexplained variation in precipitation. Differences between NCDC precipitation data points resulting from time of observation, snow–precipitation conversions, and other measurement errors are likely contributing additional variation that would be unpredictable with either mapping approach. Despite a lower correlation between observed and predicted precipitation, the average climate-imprint prediction was within ±2.5 mm, with a slight tendency to overestimate (MER = 0.01). Further evaluation of precipitation predictions on the basis of precipitation occurrence, a binary categorical variable, is required to understand how accurately the method predictively maps isolated events versus dry areas.

The climate-imprint method predicted maximum and minimum temperatures at a similar level of accuracy (±2.0° and ±1.7°C, respectively). These values are similar to MAE for daily predictions of maximum and minimum temperatures (±1.8° and ±2.0°C) reported for Daymet (Thornton et al. 1997). The slight tendency for the climate-imprint method to underpredict temperature (MER = −0.4) could bias some applications. The result that minimum temperature was, on average, 0.3°C more accurate than maximum temperatures may be due to higher accuracy of PRISM maps or lower spatial variability than for maximum temperatures. Minimum daily temperatures may also be less tempo-
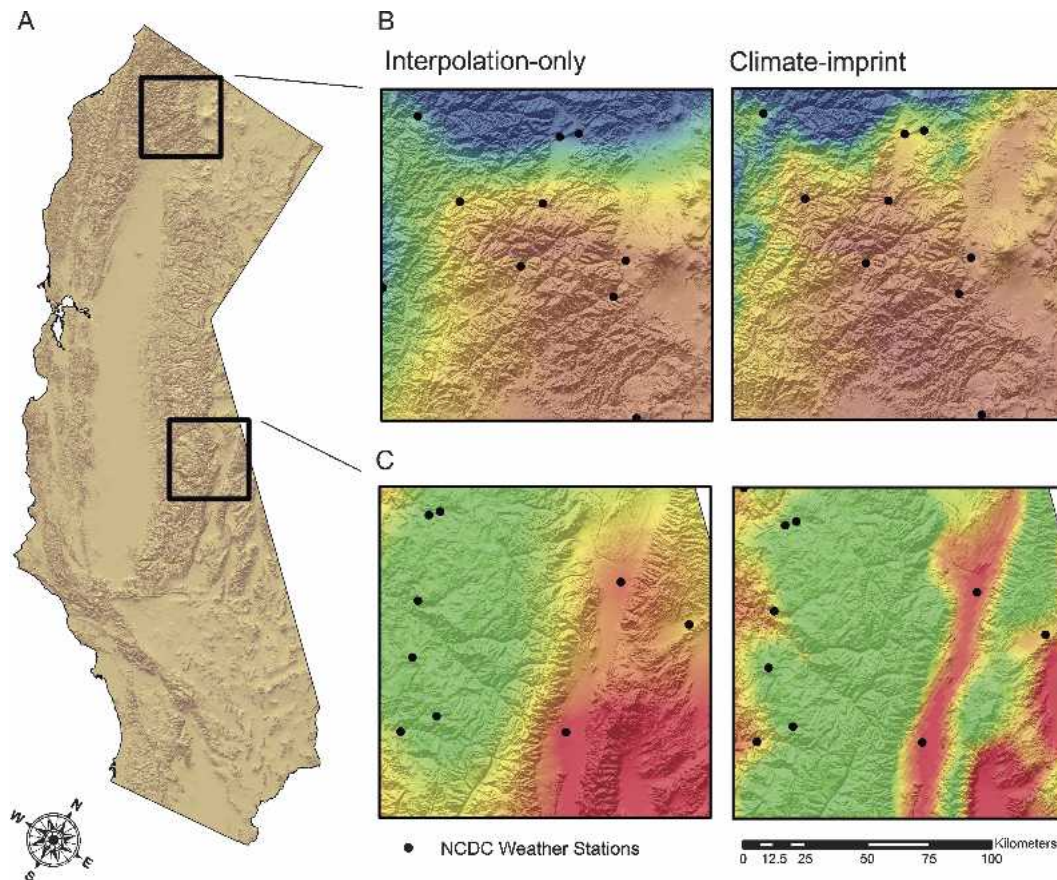
FIG. 7. (a) Locator map for large-scale comparison of interpolation-only and climate-imprint methods with base stations for estimation of (b) daily precipitation in the north Coast Ranges and (c) maximum temperature in the eastern Sierra Nevada: 26 Mar 2001.

rally dynamic than maximum temperatures. In regions outside of California, minimum temperatures could be more spatially variable and prone to error resulting from frost pockets, inversions, drainage winds, and other factors.

The result that prediction errors differ among months for all tests suggests that the model performance varies seasonally. For the climate-imprint method, March precipitation was, on average, approximately 0.5 mm lower, and January was about 0.5 mm higher, than December and February. This result may reflect differences among months in amounts of precipitation: March has the least precipitation of those in the analysis and January has the most. Error values for temperature methods also significantly differed between months, but the range of these differences was small ($<0.5°C$). March exhibited the lowest MAE value for both the climate-imprint and interpolation-only methodology, and the error in the maximum temperature estimates was higher than the error in the minimum temperatures for all four months. Accuracy dif-

ferences between months of the PRISM datasets may also account for some of the variability reported by ANOVA.

It is expected that an analysis with a systematic reduction in station number would eventually show an increase in prediction error, and vice versa. It was surprising that days with more base stations did not necessarily yield less mean absolute error than days with fewer points. For precipitation, the average prediction error was increased slightly on days with fewer stations ($r_s = -0.08$), as expected. For temperatures, there was no relationship or there was weak positive directionality (for maximum temperature $r_s = 0.07$; for minimum temperature $r_s = -0.02$). The lack of a strong relationship between error and station number suggests that the method's performance is relatively stable and is not dependent upon changes in station number from day to day. A relatively narrow range of station numbers was used in the study (130–234), which may partially explain why the expected pattern was not apparent. Alternatively, the lack of relationship between the mag-

nitude of prediction errors and the number of monitoring stations could be due to randomly changing validation stations from day to day. Because stations may also vary widely in difficulty to predict, the variation in error resulting from station numbers could be obscured. The positive relationships for temperatures could be linked with additional stations being located in locations that are difficult to predict.

In conclusion, the integration of long-term-average climate maps with point observations of daily weather conditions can improve the accuracy of interpolated maps by helping to account for the influence of varied terrain and geographic features, such as coastal proximity and orographic effects. Although the climate-imprint methods may produce predictions with different average errors by season, these differences were small relative to the overall error in the models. Moreover, the climate-imprint method generally produces consistent and stable results from day to day regardless of the variation in the number of stations present in the NCDC database. Some instability may occur during extreme weather events, which produce highly variable conditions (Parzybok 2004) that may not correspond strongly to average climate. The new method presented provides a simple yet effective approach for mapping weather conditions—a challenging task in topographically variable regions. Testing the method across the highly variable geographic regions of California did not address regional differences in error, but the results allow assessment of error in broad-scale applications. This mapping approach could provide valuable data for geographical research requiring spatially explicit maps of daily weather conditions over broad scales.

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